Autonomous Traffic Signal Control Model with Neural Network Analogy

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Abstract

We propose here an autonomous traffic signal control model based on analogy with neural networks. In this model, the length of cycle time period of traffic lights at each signal is autonomously adapted. We find a self–organizing collective behavior of such a model through simulation on a one–dimensional lattice model road: traffic congestion is greatly diffused when traffic signals have such autonomous adaptability with suitably tuned parameters. We also find that effectiveness of the system emerges through interactions between units and shows a threshold transition as a function of proportion of adaptive signals in the model.

1. INTRODUCTION

The problem of traffic control is one of the major issues of our society on motorways as well as computer networks. The problem has been of interest to both scientists and engineers. In the physics community, for example, the main interest has been in investigating the nature of the traffic itself. Different approaches have been taken, and fluid dynamical models (Lighthill & Whitham, 1955; Leutzbach, 1988), car–following models (Herman et al., 1959; Bando et al., 1995), cellular automaton models (Biham, 1992) and coupled lattice models (Yukawa & Kikuchi, 1995) have been developed. Controlling of traffic has been primarily an issue of the engineering community (See e.g., Huddart, 1996). Artificial neural network models have found many engineering applications such as in optimizations, pattern recognitions and so on (See e.g., Arbib, 1995). We believe that the traffic control problem is one

such area that can benefit from ideas and knowledge from neural network research, particularly with a diffusion of ideas stemming from other fields mentioned above. With this motivation, we propose here an autonomous signal control model which is based on a cellular automaton traffic modeling approach with an adaptive signal control mechanism in analogy with neural networks. The collective behavior of the model is investigated by computer simulations, and it is found that in a certain parameter range the adaptive model can diffuse a traffic jam. We also found that the effectiveness of the system is due to interactions between these adaptive signal units rather than as a sum of separate contributions from individual units. This is inferred from the fact that the effectiveness of the model shows a phase transition as a function of proportion of adaptive signals in the system. Even though our model shows an acceptable performance within a certain range of parameters, we are not aiming for a good engineering system to solve the traffic problem here. The main focus of this paper, rather, is to present a model designed at a cross section of the above mentioned fields so that it can serve as a possible starting point of exploration for diffusion of a variety of knowledge developed within each research area on the matter of traffic.

2. AUTONOMOUS SIGNAL CONTROL MODEL

Let us now describe our model in more detail. For simplicity we restrict ourselves here to model a one dimensional road with closed boundary condition (loop) and discrete time and step motions of cars and signals. Extension to other geometry, however, is straightforward and will be discussed elsewhere. The model road has N discrete sites. At every D distance there is a signal with U signals in total. The ith signal is characterized by two parameters, T_b^i and T_r^i, which are the duration of blue and red lights, respectively. The "cycle length" of the signal is defined by

$$T^i = T_b^i + T_r^i \tag{1}$$

For simplicity we take all the signals to have an equal "split" between blue and red: $T_b^i = T_r^i$ and $T_i = 2 * T_b^i$. We introduce M number of cars all of which go along the model one–way road in the same direction. U-turns and passing are not allowed. A car can move forward a unit step per unit time if the position in front of it is not occupied by another car. If the next position

is the signal position, it can move when both of the following two conditions are satisfied: the signal is in the blue state and the position just beyond the signal is vacant (i.e., cars cannot be at the signal position).

The main algorithm of the model is described by the following signal dynamics:

$$T_b^i(t) = \phi(V^i(t)), \quad V^i(t+1) = X_b^i(t). \tag{2}$$

$V^i(t)$ is a "potential" of ith signal at tth period and duration of the blue signal is given by a bounded non-linear mono–tone increasing function ϕ, which is taken as a sigmoidal shape:

$$\phi(u) = T_0 + \gamma \tanh(\beta u), \quad (\gamma < T_0), \tag{3}$$

where T_0, β and γ are parameters. $X_b^i(t)$ is the number of cars reaching the signal when the signal light is blue, i.e., the number of cars going through the signal position at tth period of blue light. (When a car cannot move beyond the signal because of a jam, we include it in the count.) Because of the above condition of equal split between blue and red lights, this dynamics, in effect, changes the signal cycle length T^i. The dynamics of both cars and signals are synchronous: all cars and signals are updated at each step according to the above transition rule. The dynamics of signal cycle in this model has a natural correspondence with the neural network models. Each signal is identified by an integrate–and–fire neuron (Farley & Clark, 1961; Beurle, 1962; Milton et al., 1993) and the traffic going through a signal is identified by the neural pulses it receives. The activity level of the ith neuron is identified by T_b^i which is a bounded nonlinear function of potential V^i. After each period (or firing), the potential V^i is reset to zero as in neuron models. This analogy motivates us to look into the possibility of emergent effective collective behaviors of these adaptive units, which have been observed with neural network models. In the following we show that this is indeed the case, and that the adaptive signals with the above dynamics collectively lead to the overall diffusion of the traffic congestion.

3. SIMULATION EXPERIMENTS

The traffic congestion is quantified by measuring average velocity, $\langle v(k) \rangle$. In our model, we define $\langle v(k) \rangle$ as an ensemble average of the proportion of cars which moved at time step k. More precisely, $\langle v(k) \rangle = \langle L(k)/M \rangle$,

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where $L(k)$ is the number of cars moved at time step k. When we start with random initial positions of cars and all signals with $T_b^i = T_r^i = T_0$ but with different states and phases, the T_b^i starts to change and shows non-homogeneity. Typically, the average signal period $\langle T_b \rangle$ over all signals settles to a stationary value after a transient period. The average velocity of cars $\langle v(k) \rangle$ also leads into an oscillating stationary state. Figure 1 shows one such typical example. In the figure we also compared the model with the case of all signals have a fixed period at $\langle T_b \rangle$. We observe that the adaptive signal model can retain higher collective velocity and less congestion after a transient period in this example.
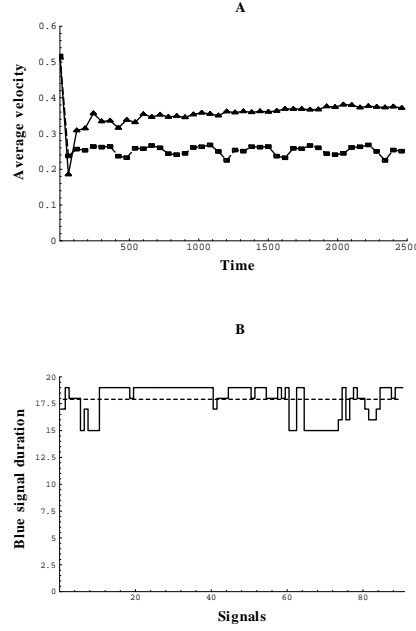

Figure 1: One comparison between the adaptive model and fixed signal period model. (A) The dynamics of average velocity $\langle v(k) \rangle$ is compared between the adaptive model (triangles) and fixed period model (squares) with $\langle T_b^i \rangle$. The parameters are set as $N = 450$, $M = 150$, $D = 4$, $U = 90$, $T_0 = 10$, $\gamma = 9$, $\beta = 0.16$, and $\langle T_b^i \rangle = 18$. Each trial started with random initial positions of cars and phase of signals and was averaged over 100 trials. (B) Distribution of blue signal duration T_b^i at 2500 steps appeared in one of the trials. The dashed line represent $\langle T_b^i \rangle \approx 18$.

This observation also holds with different car densities and parameter settings when $\langle T_b \rangle$ is sufficiently larger than inter-signal distance D. Some results are shown in Figure 2. Up to $\approx 50\%$ improvement has been observed. Qualitatively similar results are obtained for various system sizes of $N = 100$, 200, and 450.
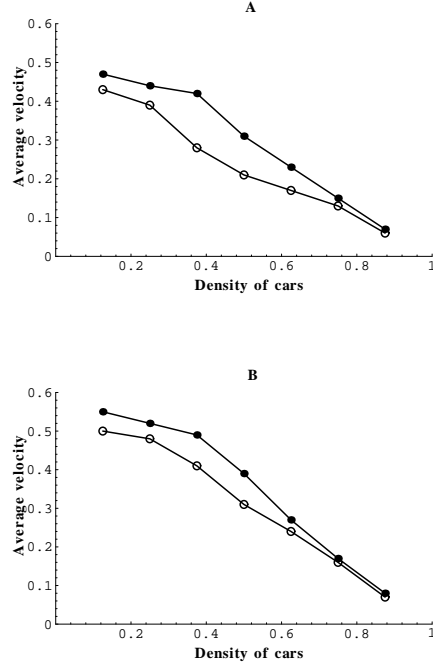

Figure 2: Examples of comparison between the adaptive (black circle) and fixed (open circle) signal period models as the density of cars $M/(N - U)$ in the system is varied, with $N = 100$, $D = 5$, and $U = 20$. The parameters are set as (A) $T_0 = 7$, $\gamma = 6$, and $\langle T_b^i \rangle = 12$. (B) $T_0 = 10$, $\gamma = 9$, and $\langle T_b^i \rangle = 18$. β for the adaptive models is tuned for each M. Qualitatively similar results are also obtained for $N = 200, 450$.

We infer from these results that the model here with suitably tuned parameters can show emergent collective organization of signal period distribution by gradually adapting to particular traffic conditions on the model road which are otherwise homogeneous.

To gain more insight into the collective behavior of the model, we investigate how performance of the model changes when we stop the adaptation

after some initial period and the signal periods are thereafter fixed. Figure 3 shows an example of the result from such simulations: there is a sharp drop in average velocity after the adaptation is stopped. This tells us that adaptation dynamics at each signal is crucial in keeping average velocity high, rather than a particular configuration of period distributions over all the signals.
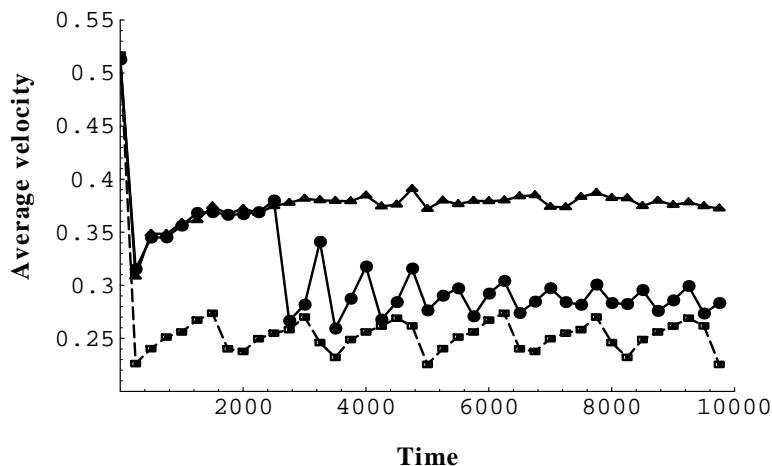

Figure 3: Example of comparison of dynamics of the average velocity. The parameters are set as $N = 450$, $M = 150$, $T_0 = 10$, $\gamma = 9$, $\beta = 0.16$, and $\langle T_b^i \rangle = 18$. They are adaptive model (triangles), adaptive model changed to fixed cycle model at step 2500 (circles), and fixed cycle model (squares).

We also looked at the case where only some portion of signals have the adaptive capability and others operate at a fixed period; a representative example is shown in Figure 4. We see that the performance of the system measured in the average velocity is quite non–linear and threshold–like as a function of the proportion of adaptive signals.

This suggests that the collective behavior of the model is not simply an aggregation of the effect of individual signals. Rather, the interaction among signals, which is indirectly mediated by cars passing through, is playing a role in the collective behavior of the model system.
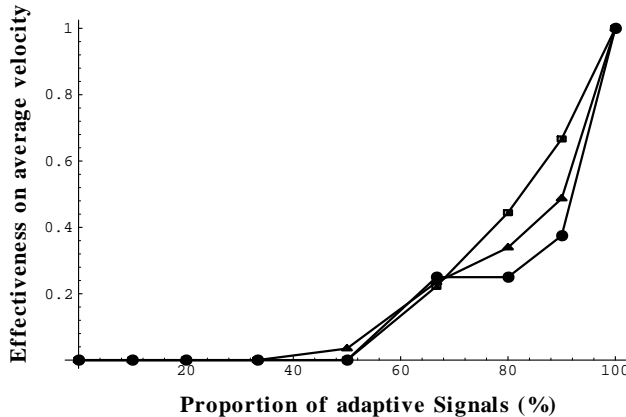
Figure 4: Change of effectiveness of average velocity as a function of propo-
tion of the number of adaptive signal units. The effectiveness is measured in
average velocity at 2500 steps and rescaled between (0,1) from no adaptive
element to all adaptive elements. The parameters are set as $N = 450$, $D = 5$,
$U = 90$, $T_0 = 10$, $\gamma = 9$, $\beta = 0.16$, and $\langle T_b^i \rangle = 18$. The number of cars are
varied $M = 100$ (squares), 150 (triangles), and 200 (circles). Qualitatively
similar results are also obtained for $N = 100, 200$.

4. CONCLUSION

The adaptive model presented here belongs to a class of models often
termed emergent computation models (Huberman, 1992; Forrest, 1991). These
models aim to derive effective computation out of interacting autonomous
local actions from each unit in the system, rather than by top–down style
algorithms or by a central control of units. Even though the guiding princi-
ples of designing such models vary, experience, concepts, and insight gained
from studies of systems showing emergent behaviors as in neural network
modelings can be quite useful particularly for the theoretical understanding
of the model, which is left for the future. It is hoped that our model with
the neural network analogy presented here can serve to call for attention to
looking at traffic control problems as another research area of neural network
community.

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